Automotive Insurance System 2019-20

AUTOMOTIVE INSURANCE SYSTEM

A Project Report

Submitted by

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Under the Guidance 0f

PROF. AVANI BHUVA

in partial fulfilment for the award of the

degree of

BACHELOR OF TECHNOLOGY

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MUKESH PATEL SCHOOL OF TECHNOLOGY

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Automotive Insurance System 2019-20

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This is to certify that the project entitled “Automotive Insurance System” is the bona fide work

carried out by Harsh Agarwal Amit Biraidar Manan Bolia and Vedang Gupte of B.Tech

(Computer Engineering), MPST1\/[E (NMIMS), Mumbai, during the VIII semester of the

academic year M, in partial fulfilment of the requirements for the award of the Degree of

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Abbreviations

CNN

RCNN

YOLO

PHP

SQL

AJAX

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Abbreviations

Description

Convolution Neural Network

Regional - Convolution Neural Network

You Only Look Once

Hypertext Pre-processor

Structured Query Language database

Asynchronous JavaScript and )GVIL

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ABSTRACT

This project aims to build an intelligent system for users to help them with their car insurance.

They can get an estimate of the insurance amount which may be provided to them from their

respective insurance companies as the “Insurance Claim Amount” to cover the damages for

their vehicle. This is very subjective as different users will have different insurance

companies/agents for their insurance and within that, a company/agent might also have different

policies for different users. The platform provided to the users is a website where they can

register and avail of its services. The user is prompted to enter basic information like car make

and model along with images of the damaged parts of the vehicle on the website. Also, the user

has to answer a questionnaire developed by us based on the learnings of the past accidents

which helps the software to know the degree or the extent of the actual internal damages

suffered by the car because of the accident. This mostly tells the software about the non-

cosmetic (engine and transmission) category of damage suffered by the car. The images are sent

to the server where a software uses Mask RCNN algorithm to analyse and detect the dents. The

estimate is calculated using previous data from the database and other problems are diagnosed

based on the information given by the user through the questionnaire. This estimate is sent to

the user as a guesstimate for the claimed amount. This project provides a quick and on-spot

approximation of the insurance amount, and thus drastically reduces the time taken to provide

an initial estimate compared to conventional approaches where the insurance company agent

would come and analyse the damage and then send a claim amount in 2-3 business days to the

user. Thus, it also strives to make the process more convenient by eliminating the need for

middlemen for an initial assessment. Now, finally, the user can decide whether he wants to go

for the insurance claim or just get his car repaired for a mechanic in the neighbourhood.

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Chapter 1

Introduction

1.1. Project Overview:

0 The objective of the project is to build a system where users can get an estimate of the

insurance amount that can be claimed for damages to their vehicle, in a small amount

of time.

0 The aim of this project is to reduce the redundant aspect i.e. human involvement

required and deliver desired results in a very short period of time.

0 Users can access the service through a website

0 Images submitted by the user through the website will be analysed by the system and

an estimate will be provided to him consequently.

0 The system can detect internal damages through a set of questions answered by the user

while the results for the damage are being calculated.

0 As a result, the system will provide the complete cost to the user.

1.2. Hardware Speciﬁcation

The hardware specifications of the system can be divided into client requirements and Server-

side specifications.

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1.2.1 Client-Side speciﬁcations

The User must have a stable internet connection for uploading images. Faster

speeds above 2 Mbps are preferred.

The device used to click images of damaged areas must be able to click high

quality images with minimum noise. 8 megapixels and high resolutions are

recommended.

The device should have an updated browser that supports FTP, HTTPS, and

other protocols.

1.2.2 Server Speciﬁcations

High Computation power

Fault-tolerant service

Load

Python environment with necessary libraries should be supported

50 GB of storage for images

The server that we have used has the following7 speciﬁcations-

Due to the unavailability of required computing resources in the free tier of major cloud

services, we decided to make our laptop as a server for backend computation.

Processor: Intel Core i7-8750H 9 MB Smart Cache 2.20GHz base processor

speed Turbo boost up to 4.10GHz

Operating System: Windows 10 Home

Memory and Storage: 16 GB DDR4 RAM

NVIDIA GTX Graphics 1050Ti 4GB GDDR5 VRAM

Storage: 128GB Fast SSD+1TB HDD

1.3 Software Speciﬁcations

0 Python 3.7 (Libraries: TensorFlow, skimage, Keras, NumPy, SciPy, Matplotlib)

0 VGG Annotator - Used to armotate damaged areas on training images.

0 XAMPP 7.3.2 - Provides a local server for the website.

0 Anaconda - Used to set up a TensorFlow environment.

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1.4 Motivation and Scope:

The number of cars in metropolitan cities is at an all-time high, and rural penetration is

increasing every day. With such an increase in the number of vehicles on the road, there is also

an increase in the number of accidents. Most of the damages are covered through an insurance

policy, but there is no clarity as to the amount that can be claimed in case of any damages. The

process for claiming insurance is long and arduous. The insurance company may take weeks to

give an estimate of the claimable amount before any repairs commence. The owner of the

vehicle may thus wish to instantly get an initial estimate. This project aims to provide an

approximate estimate by detecting the damage and using a database to derive information about

the amount that can be claimed based on the make of the car, and damages. Moreover, any

internal damage is also assessed based on a questionnaire provided to the user. This makes it

easy and convenient for a user to get an idea about what amount can be claimed. Once the final

estimate is provided, the user can decide whether the damages are worth claiming insurance for

or whether it would be more convenient to get it repaired from a local mechanic. Due to

database and system constraints, the scope will be limited to passenger vehicles manufactured

by Hyundai Motor Company.

1.5 Salient Features:

0 Users can input images of the damaged area.

0 A questionnaire is provided for assessing internal damage.

0 A possible list of problems will be emailed to the user.

0 An estimate of the claimable amount is also emailed to the user.

1.6 Guidelines:

0 Clear image with a good resolution camera

0 Cover each part individually in one image

0 Camera frame should contain only the required part.

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Chapter 2

Review of Literature

2.1 Efforts by Insurers

The following papers were read to get a clear idea of the ground reality in how insurance claims

are processed and the existing efforts by insurers to digitize the process of insurance surveyance

and whether any implementation similar to the proposed idea has been carried out. It was

essential to get a clear idea of the various policies for estimating damages. We also tried to

analyse various policies to gain information about the conditions and threshold of damages after

which the part is completely replaced by a new one.

Table 2.1: Insurance claim technologies

Author(s) Title Aim Findings

Ravi Malhotra, Swati Machine Learning in Summarize the Machine learning can

Sharina, Insurance different ways in be used for claims

Accenture which machine processing. But due to

learning is used by associated

insurers investments and risks

it has not been heavily

adopted by insurers

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ICICI Lombard Intraspect: Instant Develop anautomated This approach uses a

claim approval claim processing video recording to

software to eliminate analyse the damage to

physical inspection the car. It is not

possible to send a

picture of only

affected areas.

Madan Mohan Dutta, Factors Affecting Summarize the factors Learnt about different

Gautam Mitra Auto Insurance in that affect insurance types of insurance

India premiums and claims policies for

automobiles

Major factors that affect the insurance premiums and claim amounts are -

Geographical location - Tier 1 cities have higher premiums for the same vehicle

compared to tier 2 or small towns.

Insurance type- Insurance policies vary a lot. The number of items and parts that are

covered in case of an accident is different depending upon the type of policy. For

example, a comprehensive policy may cover plastic parts like the bumper but another

may only cover critical mechanical parts.

Vehicle details- The make, model, year of manufacture and type of fuel and age.

The buyer’s experience and past history with the insurer.

Modifications if any, may void the claim and increase premiums

Accenture is currently proposing to build a machine learning based software for insurance

claims processing, advice, fraud detection, and risk management. However, they have not yet

partnered with any insurance agency to develop the same.

ICICI Lombard uses a video to identify the damaged parts of the car. Frame by frame analysis

is done to extract the region of interest. This method is not suitable for our project since videos

occupy much more space on servers. Moreover, analysis of an entire video will require

significant computation which is not available to us. Hence, we decided to gather knowledge

about dent detection using images from other sources.

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2.2 Existing Dent Detection Technologies

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We decided to learn about existing technologies that are used by manufacturers to detect ﬂaws

in the panels of their cars. This helped us get an idea of the industry standards and assess

whether these could be used in the project for dent detection.

Table 2.2: Dent Detection Technologies

Author(s)

Title

Aim

Findings

Laura Arnal, J. Ernesto

Solanes, Jaime Molina, Josep

Detecting dings and

dents on specular

Dent detection

Using well-known

Fast enough to meet

assembly line

machine algorithm

Tornero car body surfaces optical ﬂow industry standards.

based on optical algorithms and the Resource intensive

ﬂow deﬂectometry and also requires

principle specialised

equipment. Carmot

detect scratches

T. Lilienblum, P. Albrecht, R. Dent detection in Automatic dent Fast and accurate

Calow, B. Michaelis car bodies detection for but requires prior

unpainted panels knowledge of exact

dimensions of parts.

Fails if the paint is

damaged, and

cannot detect

scratches

Qinbang Zhou,Renwen Chen, An Automatic Almost 100%

. . . Classification of

Bm Huang, Chuan L1u, J1e Surface Defect accuracy and

. . . dents and scratches .

Yu, X1aoq1ng Yu Inspection System already used in the

. by feature .

for Automobiles automotive

. . extraction and a .

Us1ng Machine industry. It can

su ort vector

Vision Methods pp differentiate

between dents and

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scratches, and also

estimate the size of

deformations.

However, it

requires

specialised,

expensive

equipment and

cannot work using

smartphone

cameras

Arjun Yogeswaran and Pierre

Payeur

3D Surface

Analysis for

Automated

Detection of

Deformations on

Automotive Body

Panels

Dent detection

without prior

knowledge of parts

Reasonably good

accuracy. Can work

on a variety of cars.

Does not work well

if the design of car

panels naturally

includes many

edges or protrusions

and detects false

positives, and

cannot differentiate

between dents and

scratches

The common issue in most of the algorithms already used is that they require speciﬁc equipment

and lighting conditions to work. This is possible in an automobile factory however, it is outside

the scope of this project. An imposed requirement in this project is that the user should be able

to click pictures of the damaged car panel using a smartphone camera, at a variety of angles and

distances. Other factors like lighting conditions are also not controllable as they are on the user

side.

[11] This paper comes the closest to achieving our goal as it does not require prior knowledge

on the dimensions of parts and still detects scratches and dents. However, it uses specialised

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equipment for detection. Instead of this equipment, we decided to look into neural networks as

suggested in [13] for comparison and dent detection.

2.3 Algorithms Using Neural Networks

Since the established algorithms used in the manufacturing process require an exact knowledge

about the dimensions of the panels, we could not use them due to lack of part specifications.

Hence, instead of looking at specific dent detection algorithms, we decided to gather knowledge

about general object detection algorithms. We decided to look into neural networks since we

could train them to sufficiently identify the damages on the car panels based on our image

dataset. To choose exactly which algorithm would be suitable for our purposes, we went

through the following research papers.

Table 2.3: Neural network algorithms

in real-time

Author(s) Title Aim Findings

Domen Racki, Dejan The effect of different Compare different CNN architectures

Tomazevia Danijel CNN conﬁgurations approaches of CNN were compared for the

Skocaj on textured\_su1~face and its performance detection and

defect segmentation segmentation of

and detection textured surfaces. It is

performance not useful for dent

detection as it is very

complex and segments

handle and other

protrusions as well

which is not required

Geethapriya. S, N. Real\_Time Object Implement “You only It is useful for fast

Duraimurugan, SP. Detection with YOLO look once” and define detection of objects in

Chokkalingam set up and parameters videos but lacks in

accuracy and finding

small objects

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Shaoqing Ren,

Kaiming He, Ross

Girshick, Jian Sun

R-CNN:

Real-Time

Object Detection with

Faster

Towards

Region Proposal

Networks

Using Faster RCNN

for object detection

Faster RCNN uses a

selective search

algorithm to identify

region proposals. The

regions are then

reshaped using RoI

pooling layer, which is

astronomically faster

than earlier

approaches

Kaiming He Georgia

Gkioxari Piotr Dollar

Ross Girshick

Mask R-CNN

Using Mask RCNN

for object detection

It is useful as it

instance

with

provides

segmentation

very good accuracy

and fast detection so it

is very useful

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,..-\_; .L,.-LAJL.

.LLM‘I

S x S grid on input

I

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Bounding boxes 4» conﬁdence

Class probability map

Fig 2.3.1: [14] Working of YOLO

Final detections

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YOLO algorithm is based on regression technique of detection, i.e. instead of doing the

detection in two stages, the algorithm does it in one pass. It directly predicts bounding box and

classes of the image, instead of first finding Regions of Interest (RoI).

YOLO divides the image into grids of m by In cells and each cell has to predict 11 number of

bounding boxes and each bounding box is assigned a confidence value that represents

probability of object being in the that box. “[15] YOLO divides the image into regions and

predicts bounding boxes and probabilities for each region. These bounding boxes are weighted

by the predicted probabilities.”

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Scale 1

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Reudual Birxk

Detection Layer

Scale? [ '

Stride 16

Upsampiirlg Layer

- runner Layers

YOLO v3 network Architecture

Fig 2.3.2: [16] YOLO Network Architecture

It is particularly fast, which makes it good for detection in videos, but it lacks in accuracy for

small objects which make it not so viable for our application as there is possibility of small

damages like dings and scratches.

Mask RCNN is based on the Faster Regional Convolutional Neural Network. It is majorly used

in applications where instance segmentation is a requirement. MRCNN works in two stages

and both of them are connected to the backbone. In the first stage, it predicts regions where

there could be an object in the input image and then in second stage, it starts predicting bounding

boxes, object classes and pixel level masks for each proposed object.

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1: I

i: I

i ,: Peg:::;ion classification

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i, I

{h I

K I ‘Fully connected

{ | layers

3:

i Fixed Size feature map

I

——————————— ROIAlign layer

Feature map

convolutional b3{kbone

Faster

r-------1

--------------J

Fig 2.3.3: [17] Architecture of Mask R-CNN

In the first stage, a light weight neural network called Region Pooling Network (RPN) scans all

Feature Pyramid Network (FPN) top-bottom pathway called feature map and predicts regions

which may contain objects. To represent the location of these regions in the input image,

anchors are used. “[18] Anchors are a set of boxes with predefined locations and scales relative

to images.” According to some Intersection over Union (IoU) values, bounding boxes and

ground-truth classes are assigned to each anchor. Also anchors of different scales are bind at

different levels of feature map, RPN uses anchors to propose where in the image there is an

object and what its bounding box should be.

In second stage, another part of neural network is used to predict the classes, bounding boxes,

pixel-level mask for each object. This neural network takes proposed object regions from

previous neural network RPN and then scans those regions and predicts object classes,

bounding box and mask for each object above a confidence value. It looks similar to previous

stage but it uses a different method called ROIAlign. Using ROIAlign removes the need of

anchors in second stage and network can locate areas of feature map. There is a separate branch

for generation of pixel level mask for each object.

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conv ’

Fig 2.3.4: [19] Working of Mask R-CNN

A Faster RCNN

- sso

. YDLO

Accuracy 0 Fast RCNN

Speed

Fig 2.3.5: [20] Comparison of Neural Network Algorithms

After careful comparison of all these methods, we decided to go ahead with Mask Regional-

Convolution Neural Network (Mask R CNN) as it provides instance segmentation with good

speed and accuracy than other object detection algorithms. It is better than the YOLO algorithm

as YOLO does not detect small objects and without good accuracy while Mask R CNN does

this successfully. Although Faster and Fast RCNN have greater speed, they lack accuracy which

is compensated by Mask R CNN.

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2.4 Web scraping

To create a dataset for training, we needed to gather images from the internet. Web scraping

can be used to collect this information. We studied some papers to gain knowledge of how web

scraping works.

Table 2.4: Web Scraping methods

Author(s)

Title

Aim

Findings

Anand Saukar, Kedar

Pathare, Shweta Gode

An Overview on Web

Scraping Techniques

Brieﬂy summarize the

different approaches

There are many tools

available online to

and Tools to web scraping scrape data from the

web. Html parsing and

simple copy-paste can

also be used to gather

required data

Pratiksha Ashiwal, Web Information Implement a Web BeautifulSoup can be

S.R. Tandan, Priyanka Retrieval Using scraping algorithm used to scrape images

Tripathi, Rohit Miri Python and using python from the internet.

BeautifulSoup Search criteria can be

modified easily and it

is very fast

[2] This paper suggests many tools like Mozenda, Visual Web Ripper, Web Content Extractor,

Import. i0, and Scrapy to scrape images. Software like UiPath can also be used for web scraping.

However, there can be issues associated with licensing and other costs.

[10] This paper suggests a simple approach that uses python libraries to implement web

scraping and is easily configurable, hence we have used this approach.

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Chapter 3

Analysis and Design

3.1 Use Case Diagram

To use the I-Bot services, the user opens the website ‘i-bot.ml’. Ifthe user is new to the website,

he will have to register himself, to begin with. If he has already registered himself, then he can

continue with logging in to his account. On successful user authentication, the user is allowed

to access the services.

To start with the claim estimation, he will have to upload images of his car and answer the

necessary questions to proceed. The server will read the input images and the user’s response

to certain questions. The damage detection algorithm is run on the input images to detect the

damaged area. Based on the detected damage (both internal and external), the cost of repair is

calculated and a report is generated for the same. This report can be accessed by the user

whenever required, by logging into his account.

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AUTOMOTIVE iNSURANCE ESTIMATOR

Register

; <extend»

/«inC|Ude):

/ Enter car and insurance details

/

/

/

xhx

CUSTOMER \

Upload Photos

\ +Takes l0

Reads query

\

Identities damages

\

Estimates cost \_\_

/ Sewer

View Report

[I «extend»

\l/

Give Feedback

Fig 3.1: Use Case Diagram showing the overview of the proposed system.

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3.2 Sequence Diagram

3.2.1 New Claim

interaction New Claim )

User Application User Interface Server

seq Authentication J

1:Login Or Register

3 : Authenticate User

12 ' Upload Successful

6 ll Fallure Ask For Reautlientication :

seq Vehicle Selection ,l

i 7 Chum O'm” ; i a Fetch Vehicle Details

L isplay Vehicle Details

: lCl Upload Vehicle Pictures and Answer QUESIIUI‘lIlEUI'E = . lJ. Generate New Claim Report

:‘g ...............................................................

EC """"""" 1' 4HS-Ei1El-Fiep-Cirt """"""" 13 : Process Claim

15 : Display Report

\_..\_.]:\_\_\_\_\_\_

Fig 3.2. 1: Sequence Diagram representing steps for raising a new claim/estimate request

The first step is user authentication. The user will register if he is new to the website or login if

he has already registered himself. The login or registration details entered by the user in the

application interface are forwarded to the server. The server performs necessary checks to verify

authenticity of the user. An appropriate message is then sent from the server to the Application

User Interface which notifies the user about the same.

Once the user is granted access to his account, he is allowed to upload images and is asked

certain questions. Based on the user’s input, a claim report is generated and provided to the

user.

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3.2.2 Server-Side

interaction Server Side J

Master Module Damage Assessment Report Generator

. Send Pictures ; : :

2 : Identify Body Work Damages

3 Send Body Work Damages 4 ' Assess External Damages

5 Send Questionnaire

' 6 Assesslnternal Damages

7 'Send All Damages

8 Request Part prices

: l-ﬂ Calculate Insurance AI'IIOLII'IIE

Dju 6 R...

LI 12 ' Send Report

. :

Fig 3.2.2: Sequence Diagram representing steps taken by the server for processing a claim

request

On receiving data from the user, the master module sends the images to the image processor

which detects the damages. The damage assessment module estimates the internal damages

based on the questions answered by the user. All the damages detected and estimated by the

image processor and the damage assessment module are sent to a report generator. The report

generator module fetches the price of the damaged part from the database. Finally, after

receiving the price, it calculates the final cost and generates a report.

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Chapter 4

Methods and Implementation

Implementation of the project begins with the process of database creation. The database for

this project comprises images of cars with superficial damages. The database building process

involves three steps:

1. Data Gathering

2. Data Cleaning

3. Data Annotation

4.1 Data Gathering

The first step was gathering images for the training set. Images of cars with damaged panels

were scraped using the BeautifulSoup package which is popularly used for parsing HTIVIL and

)GVIL documents. The images were downloaded from the Google Images webpage. A webpage

is inspected to check under which tag and class, our subject of interest reside. The python code

is run on this URL with the tag and class as parameters. On a successful run, it will download

and save all the images under the specified tag having that particular class name to your local

folder. This complete set of images that are downloaded will have data that is irrelevant, for

example, advertisements, paid placements, etc. Now the next task is to delete this irrelevant

data and obtain a final usable dataset.

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4.2 Data Cleaning

This step is necessary as incorrect data leads to false conclusions. Hence, it is important to

create a cohesive database. Data cleaning involves identifying incomplete, incorrect, inaccurate

or irrelevant parts of the data and then replacing, modifying, or deleting the dirty or coarse data.

Since our dataset consisted of images that included different classes of irrelevant images, they

had to be manually inspected and removed.

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Fig 4.2.1: Web scraping output

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Fig 4.2.2: Cleaned dataset

4.3 Data Annotation

Once the dataset is cleaned and ready to use, it needs to be armotated before it can be used as a

training dataset. Data armotation basically deals with the labelling of data (images in this case)

so that it can be used by machine learning algorithms. The images in the dataset were armotated

using the VGG armotator.

VGG armotator is a free data/image annotation tool. The annotation process involves uploading

the image dataset to the VGG armotator. Once these images are uploaded, you need to select

every individual image and demarcate the damaged area using a free polygon tool. When

demarcation is done for all the images in the dataset, a J SON or a .csv file is created based on

your preference. This file includes data of the demarcated area (damaged area), in the format:

{“filename” + ” file size” + ” shape attributes {“coordinates of the vertices of that shape”}”}

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Fig 4.3.1 VGG annotator

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11ne","all\_points\_x":[165,167,178,191,205,211,195,189,186,175,170,

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73, 70, 112],"a11\_p01nts \_y":[68, 67, 64, 65, 9L 119,142,145,145,135,133

113, 9L 81, 68]},"region attributes":{"Type": "Dent"}}],"f11e attrib

Fig 4.3.2 JSON file

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The next step was gathering an estimate of the part costs for each type of vehicle. We visited 3

local garages and 2 authorised service centres to get an approximate estimate of the labour

charges for replacement of each part. The cost of denting and painting was derived from

averaging out these costs for each vehicle. The actual prices of the parts were taken from the

official company brochures and online sources. A database was then created with all the

calculated costs. Xampp was used to store this data at the server-side in a table.

@Senrer. 127.1101 » . Database: but a .Table: parts

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\*—T—\* V id name price Car Paint cost

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I. :94“ Edit ii Copy I6 Delete 3 Fender 4586 Santro 1375

I. if Edit ii Copy @ Delete 4 Front bumper 5969 Santro 1790

I. if Edit ii Copy a Delete 5 Rear bumper 10268 Santro 3080

I. if Edit :‘ag-i Copy 6 Delete 6 Front door 18965 Santro 5689

I. if Edit ii Copy a Delete 7 Rear door 18965 Santro 5689

I. if Edit ii Copy @ Delete 8 Headlight 6532 Santro 0

I. ,5? Edit ii Copy 6 Delete 9 Tail light . 3629 Santro 0

I. if Edit ii Copy @ Delete 10 Front Windshield 11573 Santro 0

I. if Edit ii Copy a Delete 11 Rear windshield 12000 Santro 0

I. 44’ Edit ii Copy @ Delete 12 Front foglamp 4506 Santro 0

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I. if Edit ii Copy @ Delete 14 FrontSidewindow 651 Santro 0

I. if Edit ii Copy a Delete 15 Rear Sidewindow 651 Santro 0

I. if Edit ii Copy @ Delete 16 Tailgate 6242 Santro 1872

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I Console

Fig 4.3.3 Part details

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4.4 Damage Detection

For the damage detection module of the proposed system, we have developed a Mask Re gional-

Convolution Neural Network (MRCNN) using the python’s TensorFlow library with Keras as

a base for the model.

Training:

To train the network for detection we used a 150-image set as training and validation inputs for

100 epochs, 500 steps per epoch, using coco weights as the base. First, training the head layers

for 50 epochs and then for 100 epochs all layers of the network were trained. Larger no of

training epochs was desirable but not achievable due to the processing constraints of the

available training machine. The learning rate supported by TensorFlow is between 0.001 and

0.002, as rates greater than 0.002 cause an explosion in weights and then the model is not trained

properly. After 100 epochs, our server could not handle the load.

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model.trainﬁdataset\_tra1n, dataset\_val,

print{"TPain all layers")

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Fig 4.4.1: Training

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The exact specifications that we finalized were-

Backbone: Resnet50

Learning Rate: 0.0015

Steps Per Epoch: 500

Validation Steps: 50

Weight Decay: 0.0001

Number of Epochs trained for head layer: 50

Number of Epochs trained for all layers: 100

During the training of the model, the following parameters are observed:

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an\_bbox\_loss

Mrcnn\_class\_loss

Mrcnn\_bbox\_loss

Mrcnn\_mask\_loss

O 20 4O 6O 80 100

Number of Epochs —

Fig 4.4.2: Total training loss

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Log of Loss —>

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Number of Epochs —

Fig 4.4.3: Total validation loss

The classification loss values are basically dependent on the confidence score of the true class,

hence the classification losses reﬂect how confident the model is when predicting the class

labels, or in other words, how close the model is to predict the correct class. In the case of

mrcnn\_class\_loss, all the object classes are covered, whereas in the case of rpn\_class\_loss the

only classification that is done is labelling the anchor boxes as foreground or background

(which is the reason why this loss tends to have lower values, as conceptually there are only

'two classes' than can be predicted).

The bounding box loss values reﬂect the distance between the true box parameters -that is, the

(x,y) coordinates of the box location, its width and its height- and the predicted ones. It is by its

nature a regression loss, and it penalizes larger absolute differences (in an approximately

exponential manner for lower differences, and linearly for larger differences - see Smooth Ll

loss function for more insight). Hence, it ultimately shows how good the model is at locating

objects within the image, in the case of rpn\_bbox\_loss, and how good the model is at precisely

predicting the area(s) within an image corresponding to the different objects that are present, in

the case of mrcnn\_bbox\_loss.

The mask loss, similarly to the classification loss, penalizes wrong per-pixel binary

classifications (foreground/background, with respect to the true class label). It is calculated

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differently for each of the regions of interest: Mask R-CNN encodes a binary mask per class

for each of the ROIs, and the mask loss for a specific R01 is calculated based only on the mask

corresponding to its true class, which prevents the mask loss from being affected by class

predictions

Detection:

To display the detected damage area, we have tested two techniques. The first method is such

that the whole image is converted into grayscale and only intensity values of those pixels inside

the detected area are retrieved from the original image. The second method is that a mask of a

different colour than that of the detected area is drawn over the detected area.

Fig 4.4.5: The output image using the first method.

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Fig 4.4.6: The output image using the second method

The second method in Fig 4.4.4 gives a more natural look to the image and the damages are

distinctly coloured to avoid confusion. Thus, we have chosen to go with the second method for

marking damages on the car panels.

4.5 Integration of Front-End and Back-End:

When the user clicks on the submit query button, a python file is called and a parameter

containing the name of the new folder created is passed to the called python script.

Fig 4.5.1: Code for python script caller

On execution of pcaller.py, a command-line interface starts execution of executor.py and passes

the received parameter as argument “subset” to the called python script.

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Fig 4.5.2: Pcaller.py code snippet

Executor.py calls Car.py which is the main module for damage detection. On execution, Car.py

returns the damage detected as a percentage of the total area to executor.py in the form of a

dictionary.

Fig 4.5.3: Executor.py code snippet for detection module call

On receiving the result from Car.py, executor.py converts the python dictionary into I SON

format and calls the calculator.php script, whose functionality is to get the J SON file, process

it and store the processed result in the database.

Fig 4.5.4: Executor.py code snippet for passing result

Calculator.php takes the damage percent and uses an algorithm to calculate the repair / replace

cost of the part and stores it in the database.

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4.6 Website

The technologies used for the creation of the web page user interface so far are: -

Bootstrap 4.0:

The whole web page is styled with Bootstrap using the containers provided by the bootstrap,

the navigation bar, the footer, and the hero tag.

JavaScript:

Mostly the backend work for the animations and effects of smoothness of the user interface is

done using JavaScript, for e.g.: the sticky navigation bar is made using JavaScript.

Cascading Sﬂle Sheets 3:

The inline and in-tag styling is done using the in-line CSS and some specific colours are also

put in the backgrounds using CSS since bootstrap wasn’t offering as many options in colours.

PHP:

PHP is used for the backend coding for the Website for the login and new user registration

facility. Also, the data retrieval of a user will also be through PHP only.

SQL:

The database we will be using to store the general details of a user and his answers to our

questionnaire will be stored in the SQL database.

AJAX:

Asynchronous loading of web content- Used to asynchronously attach web content in the DOM

tree without reloading

Angular J S :

Used for data binding and dynamism in our website.

jg zueg:

We have used jQuery to implement various animations and transitions on the website.

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REGISTER

Fig 4.6.1: Registration Page

HOME ABOUTME CALLERV MVMASTERS CONTACNS

WELCOME TO THE INSURANCE BOT!

Welcome to the Insurance Bot! Get a repair cost estimate for your

damaged car in no time and save yourself the hassle of going to

your insurace agent and waiting for him to tell you the claim

amount by getting a very close approximate of the amount by us!

LOGIN TO GET STARTED!

Fig 4.6.2: Home Page

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Fig 4.6.3 : Login Page

HOME ABOUT ME GALLERY MY MASTERS CONTACT US LOGOUT

HELLO MANAN BOLIA!

You can find steps in the about me me section if you want to know the

procedure and whenever you are ready click on the button below...

GET ESTIMATE NOW!

Fig 4.6.4: User’s Home Page

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l—Ovi L sweat-Isa LOGOJI

Please add a part to proceed...

Part that has been damaged:

Select Part

Please select your car:

Select car

Select image to upload:

Choose File No ﬁle chosen

Fig 4.6.5: Initial inputs for report generation

our :Aslinc Ana ioCauT

Please add a part to proceed...

Please select your car:

Crew

Part that has been damaged:

I Select Part

Selea Parr

Front Bumper

Rear bumper

Tailgate

Front door

Rear door

Fender

Fig 4.6.6: Selection of damaged part

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Please answer the following question to

help us build a better report!

I3 Is the front damaged?

u Is the side damaged?

a Is the rear damaged?

Fig 4.6.7: Questionnaire step 1

HOME DASHEUAPD LOGOUT

help us build a better report!

[1 Are the head-lights damaged?

[1 Are the front fog-lights damaged?

C: Is the car stalling or not starting properly?

[1 Is the car changing direction without steering input?

[I Has the ride quality degraded ?

C: Is the at not working satisfactorily ?

C: Is the braking unsatisfactory?

C: Is the front windsheild shatted?

C: Is the side damaged?

Fig 4.6.8: Questionnaire step 2

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HOME DASHBOARD lOGOUI

l, Is the front windsheild shatted?

:3?“ Side for from side Window ‘damaged?

Both srdes

i Are the speakers not working?

i, Are the rims damaged?

u Is the window operation impaired?

l Is the rear damaged?

Fig 4.6.9: Questionnaire step 3

HOMI UAwnaAVu IOCOUI

c. Are the ORVM(s) damaged?

. Are the speakers not working?

, Are the rims damaged?

; Is the window operation impaired?

‘, Are the tail-lights damaged?

,, Is the braking unsatisfactory?

:1 Is the vehicle producing loud sounds?

Is smoke emanating from the vehicle?

2' Is the rear windsheild shatted?

Fig 4.6.10: Questionnaire step 4

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SUMMARY OF YOUR REPORT

Report ID: ‘IO

PanDamaged: Front Windshield

Image Upluaded: backgroundjpg

Add more parts Gate Dashboard

Fig 4.6.11: Summary of inputs

REPORTS IN PROCESSING

mm ID: 1

Car: Santro

Part Damaged: From Bumper

Image Uploaded: dashbtkipg

Part Damaged: Rear bumper

lmnge Uploaded: quelyrbckipg

Part Dnmlged: Headlight

Imago Uplouled: whole part was ieplaed‘

Report ID: 3

CM: Sanno

Fig 4.6.12: Report details

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REPORTS COMPLETED Mil

Rapon ID: 2

Car: Santm

Part Damaged: Hood

Cla im a ppmimatiun: 14848

Image Uploaded: backgroundypg

Part Damaged: Tailgate

Claim a ppmimaﬁun; 3966

Image Uploaded: Inga pug

Part Damaged: Tall light

Claim appmximaliun: 3529

Image Uploaded: Whole pail was replaced‘

Final Amount: 22443

Fig 4.6.13: Final generated estimate

HOME GAuEQr ABOUIME MlMastth LONTACTMASTERS LOGIN

Few Words About Me...

I am a super intellegeht bot designed by my masters in orderto help the

laymen who seek money from their insurance company My true

purpose is to tell them the exact amout of claim money they Will be

getting from the insurance company just follow the followmg

instructions.

FILL UP THE FORM

Te‘l me about me level afdarrlage done to yaur Ear byarlswerlrlg a

few Simple questions laid down my me in my questlonere

UPLOAD PICTURES

Up'oad the pictures of accidental parts of yourcarto the (loud so that

Iran have a rite look at them,

‘ O

WAIT FOR RESULT

Ohte i get all the data heeded by me [D anallﬂe the damage done [El

®@@

your car on the basis ofthe statistltal data \Ni’li’ﬁh I already have. well

for r"y result

Fig 4.6.14: Information page about I-bot

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ABOUT ME GAUERV DEVELOPERS CONTACT US DASHBOARD LOGOUT

FACTS

232 521 365 24

“UIIDV‘C this kccurotco'ooctcrs Cost-65m oci‘ycc’ -<o..rsolspooc't

Are you ready?

Click on the button to calculate your insurance amount.

Fig 4.6.15: Facts about previous reports

HOME sauﬂv AsouTME MVMASTERS CONTAL‘TMASTERS LOGIN

CONTACT MASTERS

9 NMIMS MPSTME,

Your Name

Ville ParlelWl,

Mtlmbal 400069

Your Errail

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u Suhlect

+91 120 6220207 Message

Send Message

Fig 4.6.16: Query form

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Chapter 5

Results and Discussion

Fig 5.1: Dent demarcated properly

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Fig 5.2: Dent demarcated properly

As it can be observed in the above images that there is proper or very small error in the area

detected as a damaged part.

Fig 5.3: Dent demarcated

As it can be seen in the image above, there is extra damage detected, which in reality is not

damaged but the shape of the car.

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Fig 5.4: Multiple damages are demarcated

Fig 5.5: Multiple Damages are demarcated

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Fig 5.6: Multiple damages but not all marked

As it can be observed in the above images, the damage detection module is able to detect

multiple damaged areas on the car but sometimes fails to identify all the damaged areas.

To increase the performance of the damage detection module, which is, increasing accuracy in

the scenarios where not all damaged areas are demarcated, the undamaged area is detected as

the damaged or undamaged surrounding of damaged areas is also considered as damaged part.

To do the improvement we need to train more layers of CNN, increase the training and

validation dataset size, increasing steps per epoch and number of epochs. The proposed

improvement steps could not be taken from the begim1ing due to the limited processing power

of the machines available with the team.

So, to increase the processing power use of cloud computing like Microsoft Azure, Google

Cloud Platform or Amazon AWS were considered. However, the processing power required

for this project was not available in the free tier of these services. We tried setting up Amazon

AWS servers but were automatically charged for using these since our processing requirements

were quite high. Hence, we have decided to stick to our existing infrastructure until funding for

better servers can be arranged.

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Chapter 6

Conclusion and Future Work

The proposed system will estimate the insurance claim amount for a car’s damage as a total

sum of both internal as well as external damages suffered by the car. This process will be carried

out without much hassle and the results will be obtained instantly. This will allow the user to

decide if he should go ahead with the insurance claiming process. The traditional way of

claiming an insurance is very long as it involves manual inspection of the car by the insurance

company agent to evaluate the damages. He will then give his report to the company.

Verification the cost of damaged is done by the company and then a claim amount based on the

coverage offered by the insurance policy of the user is provided. This whole process takes at

least 5-7 days with no guarantee that the claim amount which the user will get is sufficient to

cover most of the damages. Through our proposed system, the user can simply put in all the

details and get an approximate insurance claim amount quote on-the-spot instantly and decide

whether the amount which he will get from the insurance company is worth the wait and

inconvenience for 5-7 days or he should just go to the local nearby mechanic and get it fixed

locally if it’s costing the same, which is the purpose of this project.

This also gives you the option to decide against availing the insurance once you have seen the

estimate of the claim amount you are going to get for the damage, otherwise in case of insurance

companies, once you file the report of your car damage and get the exact claim amount, you

carmot say no to the company as they will treat it as the damage done to the car which was not

accounted for and they might cancel your insurance. Moreover, the claimant also stands to lose

the No Claim Bonus (NCB), which is a discount offered on the insurance premium while

renewing the policy if no insurance amount is claimed throughout the year. Since our project

helps the user get a decent estimate of the claimable amount without initiating the insurance

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claim, it allows the user to consider these factors beforehand. Based on the quotation that the

system provides, the user can analyse whether it is financially prudent to claim insurance, at the

cost of higher premiums, or whether it would be better to get it fixed by his/her own funds.

Hence, even though the software does not give an exact quote of the claimable amount, it greatly

increases convenience and saves the user’s time by giving an instant quotation. It is also

accurate enough to help the user make an informed choice and potentially save some money

and hassles by helping him/her decide if claiming insurance would be beneficial at all.

Future scope for this project includes:

0 Expanding the system’s capabilities and database to perform analysis on all types of car

manufacturing companies.

0 Improving the performance by setting up powerful servers which can handle more

epochs and larger training dataset.

0 Expanding the system’s capabilities to calculate the claim value based on the type of

insurance policy availed by the user.

0 The questionnaire answered by the user can be replaced by an interactive Chatbot.

0 Development of the system so as to completely eliminate the role of a middleman i.e.

the surveyor.

0 An app could also be developed to increase the reach and convenience of the system

0 Working towards a better guesstimate over time as the database increases with practical

real-life cases.

0 Getting the guesstimate given by the software more accurate, close to the actual estimate

by learning from real cases which will be added to the database simultaneously.

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APPENDIX I: Soft Code

Login Algorithm

1. Creation of HTML page which consists of:

0 Creation of title.

0 Calling CSS using bootstrap.

0 Selection of style

0 Addition of Footers and calling AJAX files.

2. CSS binding of HTML pages:

0 Selection of style

0 Positioning of tag

0 Positioning of place holders

0 Redirection to sign up.

3. Form creation:

0 Addition of header files

0 Label for usemame and password

0 Initialization of button for signing in

Register Algorithm

1. Creation of HTML page which consists of:

0 Creation of title.

0 Calling CSS using bootstrap.

0 Selection of style

0 Addition of Footers and calling AJAX files.

2. CSS binding of HTML pages:

0 Selection of style

0 Positioning of tag

0 Positioning of place holders

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3. Form creation:

0 Addition of header files

0 Label for Usemame, Password (2 times), Insurance type and company, car

make/model and contact number

0 Initialization of button for signing up.

0 Redirection to Login.

Report Builder Algorithm

1. Creation of HTML page which consists of:

0 Creation of title.

0 Calling CSS using an external style sheet.

0 Selection of style

0 Addition of Footers and calling AJAX files.

2. CSS binding of HTML pages:

0 Selection of style

0 Positioning of tag

0 Positioning of place holders

3. Form creation:

0 Addition of header files

0 Label for Usemame, Password (2 times), Insurance type and company, car

make/model and contact number

0 Initialization of inputs for adding details.

0 Taking multiple inputs using AJAX.

0 Submitting the report and redirection to Dashboard.

4. Inherent python call:

0 Calling the pcaller.py using AJAX before redirection

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Dashboard Algorithm:

1. Creation of HTML page which consists of:

0 Creation of title.

0 Calling CSS using an external style sheet.

0 Selection of style

0 Addition of Footers and calling AJAX files.

2. CSS binding of HTML pages:

0 Selection of style

0 Positioning of tag

0 Positioning of place holders

3. Data gathering and displaying:

0 Displaying user specific and report specific data through database

0 Accessing MySQL tables

0 Analysing status of reports and putting reports in respective sections.

0 Calling ongoing\_query.php for ongoing reports and comp\_query.php for

completed reports using data\_selector.php

Calculation algorithm:

1. Invoking of php script through python

0 Python script calls the python script with result.

0 Python result gets converted to associative array from json data.

0 Array fed to the script

2. Calculating service cost

0 Taking data from python and MySQL.

0 Calculation of final cost after thresholding and summation.

3. Updating MySQL database.

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Log of Loss —>

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APPENDIX 11: Visualization of loss functions

Network diagram of the project - https://bit.lv/2Uq0u5T

The link given above contains the complete Mask R-CNN network diagram used in our

project. Due to the large size of the network diagram, we have chosen to not include it in this

report.

Loss Graphs -

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Fig: Total validation loss

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Log of Loss —>

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Fig: Validation region proposal network bounding box loss

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Number of Epochs —

Fig: Validation region proposal network class loss

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Fig: Validation Mask R-CNN mask loss

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Fig: Validation Mask R-CNN class loss

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Log of Loss —>

Log of Loss

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Fig: Validation Mask R-CNN bounding box loss

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Number of Epochs —

Fig: Region proposal network class loss

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Fig: Region proposal network bounding box loss

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Fig: Mask R-CNN mask loss

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Number of Epochs —

Fig: Mask R-CNN class loss

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Number of Epochs —

Fig: Mask R-CNN bounding box loss

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Log of Loss —>

0 10 20 30 40 50 60 70 an 90 100

Number of Epochs —

Fig: Total training loss

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PUBLICATION

Title of Paper AUTOMOBILE BODY DAMAGE DETECTION USING

COD/[PUTER VISION

Author Names Harsh Agarwal, Amit Birajdar, Manan Bolia, Vedang Gupte

Publishing House 2020 International Conference on Signal and Information Processing

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